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Using Thermal Remote Sensing to Quantify Impact of Traffic on Urban Heat Islands during COVID

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16. Abstract

A three-month lockdown in the U.S. at the beginning of the COVID-19 outbreak in 2020 greatly reduced the traffic volume in many cities, especially large metropolitan areas such as the San Francisco Bay Area. This research explores the impact of transportation on climate change by using remote sensing technology and statistical analysis during the COVID-19 lockdown. Using thermal satellite data, this research measures the intensity of the urban heat island, the main driver for climate change during the urbanization process. The research team acquired morning and afternoon MODIS data in the same periods in 2019 before the pandemic and 2020 during the pandemic. MODIS imagery provides a wall-to-wall land surface temperature map to precisely measure the dynamics of the urban heat effect. In situ meteorological data were also acquired to build an urban surface energy budget and construct statistical models between solar radiation and the intensity of heat dynamics. The team implemented this urban heat budget in six counties in Northern California. This research quantifies the impact of lockdown policies on heat intensity in urban areas and human mobility in the context of COVID-19 and future pandemics. The quantitative results obtained in this study provide critical information for analyses of climate change impact on an urban scale.

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1. Introduction

In 2019, the emergence of a novel coronavirus, SARS-CoV-2, was identified as a causative agent with human-to-human transmission. Due to the absence of a vaccine or specific medical treatment for COVID-19 at the time, measures such as social distancing and public interventions in the form of lockdowns were imposed in an attempt to curb the epidemic (Cassidy et al. 2020; Huaiyu Tian et al., 2020). In an effort to prevent the spread of the novel coronavirus, various policies including lockdowns, social distancing, and the use of masks have been enforced in the United States (Huang et al. 2021; Arora et al. 2020). Lockdowns involve the restriction of movement and gathering of people in an effort to limit the spread of the virus. Lockdowns varied in severity and geographical scope, including the closure of non-essential businesses, the cancellation of public events, and the implementation of stay-at-home orders. These measures were aimed at reducing the number of people who came into contact with the virus (State of California 2020). Research has shown that these lockdowns were generally effective at reducing the spread of COVID-19 and flattening the curve. California's lockdown provided a unique opportunity to quantify the impact of transportation on urban climate change.

The Urban Heat Island (UHI) is a phenomenon where a metropolitan area has a temperature significantly higher than the surrounding rural areas (Oke 1981; Gorsevski et al. 1998). The temperature difference is typically 2–3˚C, but may be up to 11˚C. The difference is typically larger at night than during the day and is most apparent when winds are weak (Oke et al. 1999). The main causes for the UHI effect include waste heat generated from anthropogenic activities and energy usages, such as vehicle exhaust, and human and industrial activities (Kato and Yamaguchi 2005). Another cause is impervious surfaces, such as buildings, concrete, and asphalt surfaces. With little vegetation coverage, these surfaces effectively retain more heat. The UHI effect is among the best expressions of the impact of human activities on local climate (Hinkel et al. 2003), which play an important role in the climate warming trend. For example, research in China indicates that UHI contributes to about 30% of local climate warming (Ren et al. 2015).

The UHI effect is one of the most apparent consequences of environmental change induced by anthropogenic activities and an important indicator of climate change (Huang and Lu 2015). It has been reported that anthropogenic activities have caused the rise of global mean temperature by 0.8˚C compared to the preindustrial level (IPCC 2007). Despite global warming caused by greenhouse gas, the human impact on climate on a local and regional scale is much more significant (Zhao et al. 2014). Kalnay and Cai (2003) estimate there is a 0.27˚C per century mean surface warming due to land-use changes in the United States (Kalnay and Cal 2003). Research in southeast China suggests overall warming of 0.05˚C per decade for mean winter surface temperature induced by urbanization (Li et al. 2012). However, there remains a paucity of quantitative evaluation of the traffic volume impacts on urban warming, despite transportation accounting for the largest share of greenhouse emissions (28.9%) according to statistics from USEPA (US EPA).

This project aims to take advantage of thermal remote sensing to isolate and quantify the transportation impact on UHIs in Northern California's Bay Area metropolitan area during the COVID-19 lockdown. In 2020, California's major cities implemented a lockdown to control the spread of the pandemic, which cut off about half of the transportation volume compared to the normal traffic volume (Arora et al. 2020). It offers a unique opportunity to isolate and quantify the impact of transportation on the climate. We adopt thermal remote sensing that provides a wall-to-wall land surface temperature (LST) map (Weng et al. 2004; Voogt and Oke 2003), which is vital for quantitative analyses of urban temperature dynamics. Thermal remote sensing technology has been widely applied to UHI research. Moderate-resolution Imaging Spectroradiometer (MODIS) LST provides twice-daily LST measurements acquired over a certain study area at a 1 km spatial resolution (Jeganathan et al. 2011). We can retrieve the urban surface energy budget by taking advantage of the twice-daily surface temperature and ground meteorology measurements, and then construct statistical models between net radiation and both extent and intensity of heat dynamics. We examine the variation of urban heat island intensity and spatial extent by utilizing traffic variation during the COVID-19 lockdown. The quantitative results obtained in this study provide critical information for analyses of climate change on a global scale.

2. Study Area and Data

2.1 Study Area

The study area is the San Francisco Bay Area (SFBA) in Northern California, one of the most important and influential regions in California and the entire U.S. The SFBA is an economic hub with various urban and industrial functions. The area is home to many Fortune 500 companies, including high technology, finance, and biotechnology. The average median household income for the Bay Area was $79,900 in 2021, remarkably higher than the national average. The median household income for the south Bay Area (Silicon Valley) ranges from $93,370 to $154,256, the largest in California.

The SFBA has a diverse and complex transportation network, including an extensive public transit system with buses, trains, and ferries. The Bay Area Rapid Transit (BART) system is a popular option for getting around the region, with trains that serve San Francisco, Oakland, Berkeley, and other cities in the Bay Area. Many people in the Bay Area own and drive their own cars, and the region has a network of freeways and highways that make it easy to travel by car. However, traffic can be heavy in some areas, particularly during rush hour in the San Francisco area (Osman et al. 2019).

California became the first state to impose shelter-in-place orders across the whole state to protect the health of Californians and to slow the spread of COVID-19 (State of California 2020). As summarized in Table 1, on March 4, 2020, California Governor Gavin Newsom declared a state of emergency in response to the global COVID-19 pandemic (State of California 2020). To reduce the spread of COVID-19, further restrictions were implemented. With advice from public health experts, mass gatherings of 250 or more people were been postponed or canceled statewide. Then, on March 13, 2020, with an executive order from Governor Newsom, all state schools were closed (State of California 2020). Following this, senior citizens were advised to stay at home, and restaurants had to reduce seating (Cassidy et al. 2020). On March 16, 2020, the Bay Area counties declared shelter-in-place orders (Lin 2020).

Table 1. Dates that California Imposes the Lockdown or Half Lockdown

Date	Government Response
March 4, 2020	Governor declared a state of emergency
March 11, 2020	Mass gatherings (over 250 people) postponed or canceled statewide
March 13, 2020	State-funding schools closed
March 16, 2020	Bay Area counties declared shelter-in-place orders
March 19, 2020	Statewide shelter-in-place order issued – Stage 1
April 1, 2020	All schools closed for the remainder of the academic year
May 7, 2020	California moved into Stage 2 of modifying its stay-at-home order
May 25, 2020	Stage 3 of reopening with hair salons, barbershops

The stay-at-home order has potentially affected travel behavior, the use of public transportation, and caused a reduction in going out for unnecessary purposes, including the use of public transportation and non-essential outings, such as commuting to work or school. To examine the impact of the COVID-19 lockdown on traffic volume, Table 2 shows data on traffic accidents from the Transportation Injury Mapping System (TIMS) at UC Berkeley. The data shows a marked reduction in the total number of crashes during the lockdown period in 2020 compared to the same period in 2019 without the lockdown, which is attributed to the decrease in transportation due to the stay-at-home order, resulting in a reduction of personal cars and public transportation services in urbanized areas.

Table 2. Total Crashes, Fatal (F) or Severe Injury (SI) Crashes, Vehicle Miles Traveled in 2019 And 2020 in Six Counties in the Bay Area

Week Starting Date	**2019**			**2020**		
	Total Crashes	F+SI Crashes	Vehicle Miles Traveled	Total Crashes	F+SI Crashes	Vehicle Miles Traveled
10-February	233	16	463.17	185	21	480.04
17-February	173	25	471.23	177	15	476.57
24-February	220	19	467.48	183	15	485.13
2-March	209	8	470.9	179	13	471
9-March	197	15	481.08	209	15	429.6
16-March	209	13	482.69	75	10	316.46
23-March	169	12	472.43	93	12	275.21
30-March	153	8	464.45	101	10	270.1
6-April	170	15	478.57	88	14	268.36
13-April	175	12	486.41	67	10	281.85
20-April	219	20	495.43	93	17	291.36
27-April	209	20	493.16	81	7	302.23
4-May	199	16	495.75	87	15	326.7
11-May	263	20	482.73	101	11	328.43
18-May	212	20	489.36	99	14	351.22
25-May	182	16	481.39	102	10	351.35
1-June	221	15	497.32	120	19	365.51
8-June	226	22	495.49	127	14	388.94

In this study, we focused the study area on six municipal counties of the South and East Bay, including Marin, San Francisco, San Mateo, Santa Clara, Alameda, and Contra Costa counties (Figure 1). The south and east SFBA is known for its high income levels from the high-tech industry, and it is a leader in developing new technologies and products (Table 3). It is home to many major technology companies and is a hub for innovation and economic growth. Many of the world's largest and most influential technology companies, such as Apple, Google, etc., are located in this region. This region is referred to as "Silicon Valley," due to the concentration of technology companies and innovation that has occurred there.

Table 3. Population, Median Household Income, Mean Travel Time to Work, and Percentage of the Civilian Labor Force in Six Counties in the Bay Area

Bay Area Counties	Marin	San Francisco	San Mateo	Santa Clara	Alameda	Contra Costa
Population (2020)	504.1	18,629.1	1,704.0	1,499.7	2,281.3	1,626.3
Median household income (2020)	$121,671	$119,136	$128,091	$130,890	$104,888	$103,997
Mean travel time to work (min.)	31.8	33.3	29.4	29.2	34.2	38.5
Percent of civilian labor force (2020)	63.7%	71.2%	68.7%	67.6%	67.2%	64.9%

Figure 1. The Study Area with the Six Counties in Northern California

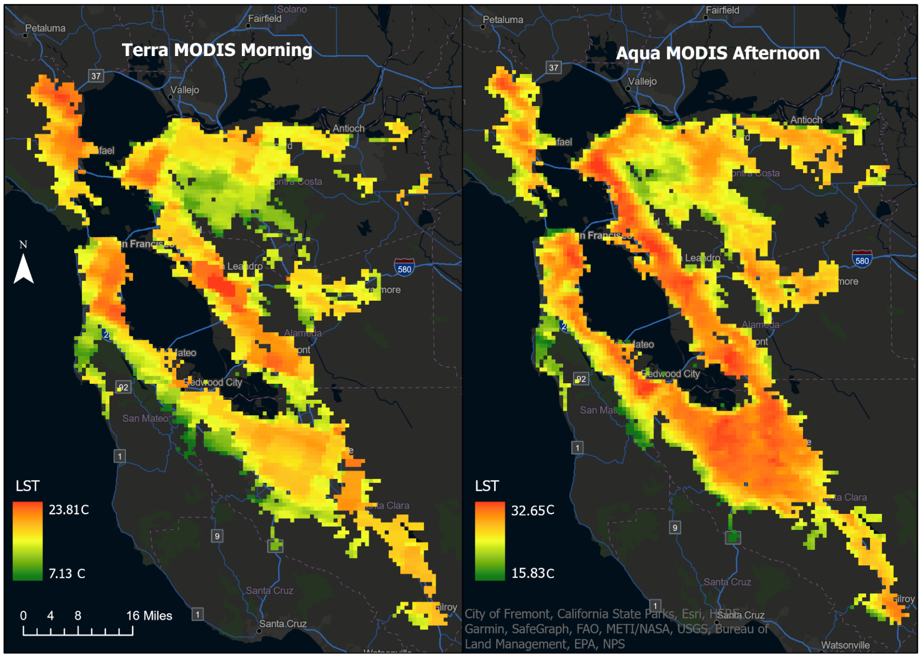
2.2 Remote Sensing and Meteorological Data

In recent UHI studies, thermal remote sensing technology, such as NOAA-AVHRR, MODIS, Landsat, ASTER, has been widely applied to UHI research (Gallo and Owen 1999; Voogt and Oke 2003; Tran et al. 2006). In contrast to meteorology data, thermal remote sensing can provide a temperature map that covers the area and is vital for analyzing the impacts of UHI over the metropolitan region (Streutker, 2002). Satellite remote sensing data can also give repeating measurements over temporal revisiting cycles and is thus suitable for temporal thermal dynamics monitoring and analysis.

We acquired both Terra and Aqua MODIS thermal remote sensing data to access the SFBA thermal environment (Figure 2). Terra MODIS satellite overpasses at 10:30 AM local time, while Aqua MODIS satellite overpasses at 1:30 PM local time (Sentlinger et al. 2008). LST images from the satellite sensor measures the long-wave thermal radiation emitted from the Earth's surface, which is related to the solar radiation absorbed by the Earth's surface. Nevertheless, radiation absorbed by the Earth's surface differs between morning and afternoon. The mean temperature of the afternoon LST image is significantly higher than that of the morning image, given that LST acquired time is 10:30 AM and 1:30 PM for the morning and afternoon groups, respectively.

The MODIS LST v6 products provided by NASA have undergone atmospheric correction with *in situ* meteorological data, and the accuracy of the LST is better than 1°C in most cases (Wan 2014). We selected tie points around dark waterbodies to refine the geo-locations of the time series MODIS images for their spatial co-registration. The MODIS image scenes have been cut to cover the SFBA case study area (Figure 2). We examined daily Terra and Aqua MODIS LST image products for three months from March 1 to May 31 in 2019 and 2020 (Figures 3 & 4).

Figure 2. Land Surface Temperature in the South Bay Area on March 2nd, 2020 (Celsius)



Three hundred and sixty-eight MODIS images were screened, and 124 images were selected (Table 4) based on the data quality and cloud coverage. Images with more than 10% cloud coverage, or if they were acquired in high wind speed conditions, were excluded. A large number of images were excluded due to the excessive cloud coverage and not included in our subsequent analysis. Figures 3 and 4 show the selected cloud-free MODIS images for the Bay Area in 2019 and 2020, morning (Terra) and afternoon (Acqua) groups.

Table 4. Cloud-free Terra and Aqua MODIS Image Data

Daytime	Terra (Morning)		Aqua (Afternoon)	
Time period	03/01–05/31 (2019)	03/01–05/31 (2020)	03/01–05/31 (2019)	03/01–05/31 (2020)
Total images	92	92	92	92
Cloud-free images	30	29	33	32

In situ observations on solar radiation were used to model the effect of solar radiation variation on the LST in order to isolate the effect of traffic volume variation. We utilized solar radiation data acquired from a meteorological station, Moraga, in the Bay Area at a latitude of 37.84°N and a longitude of 122.13°W (Figure 1). The station is part of the network of the California Irrigation Management Information System (CMIS). Solar radiation intensity measured at the station is considered representative of the entire Northern California area in a unit of W/sq.m*2.065 per day.

Daily temperature, humidity, wind speed and direction, and sun illumination hours were also measured at the station.

Figure 3. Urban Land Surface Temperatures (˚C) Time Series in North California in 2020 for the Morning Group (left) and Afternoon Group (right)

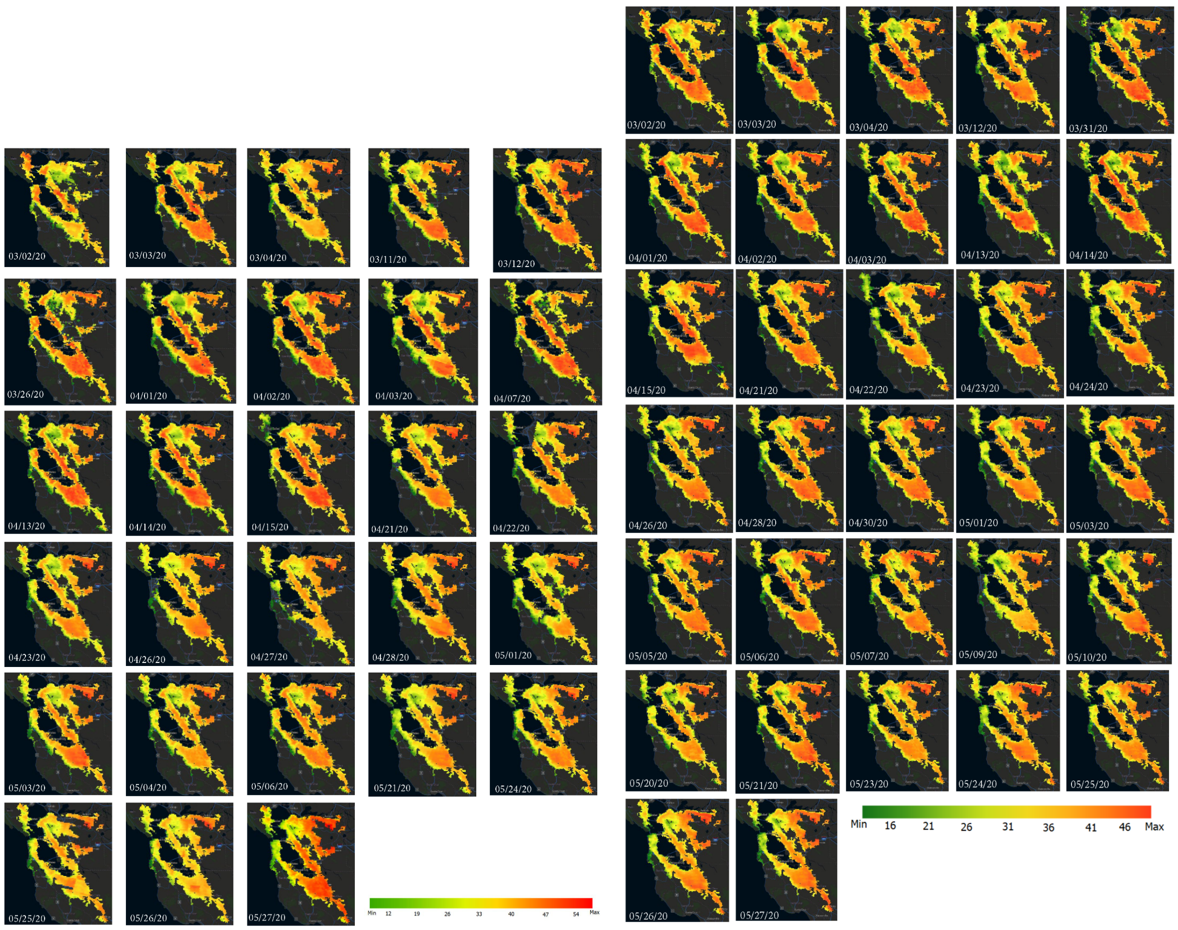
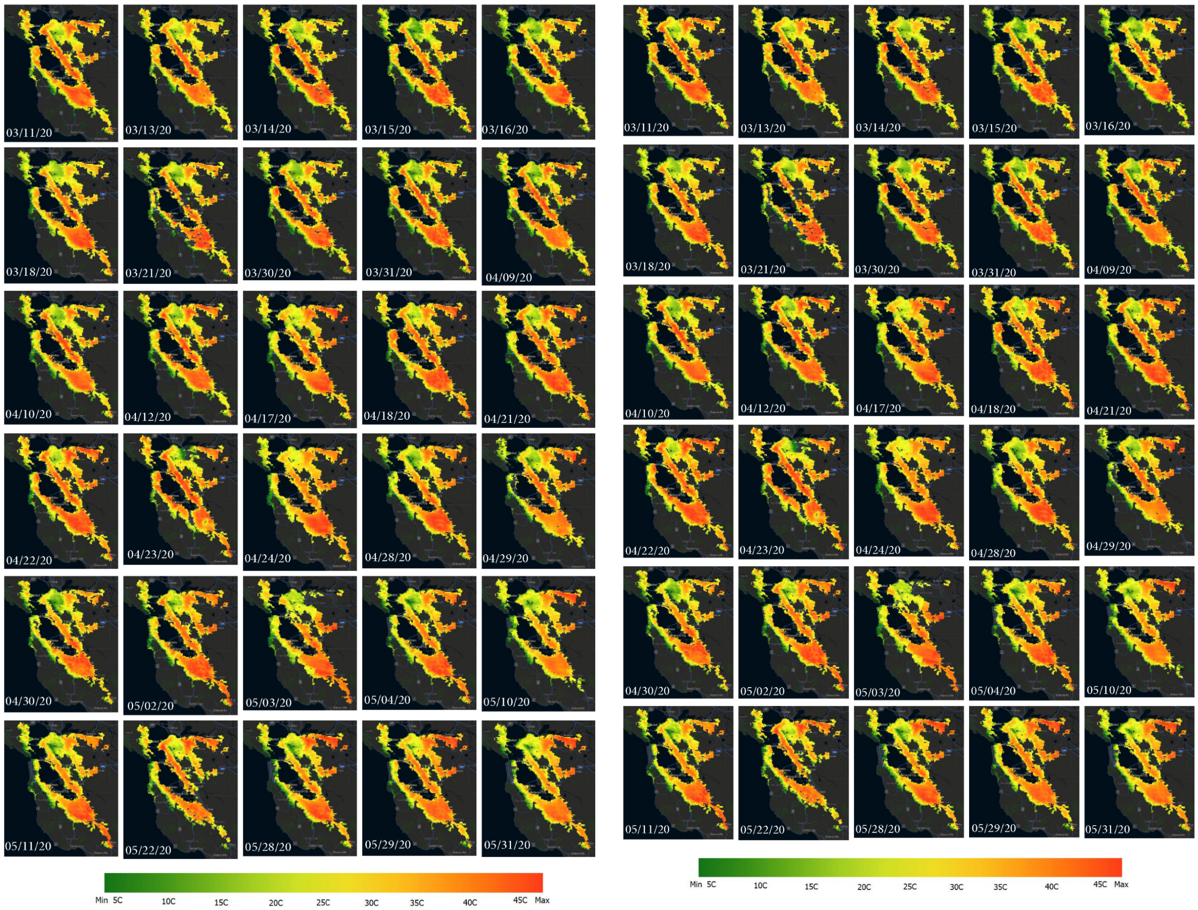


Figure 4. Urban Land Surface Temperatures (˚C) Time Series in North California in 2019 for the Morning Group (Left) and Afternoon Group (right)



3. Analysis and Results

3.1 Multiple Regression Models with Dummy Variable

A "dummy variable" is a useful method of introducing a regression analysis contained in variables that are not conventionally measured on a numerical scale (Allison 2002). The use of dummy variables requires the imposition of additional constraints on the parameters of the regression equations if determinate estimates are to be obtained (Hardy 1993). In fact, the independent variables specified in a regression equation can include any combination of qualitative and quantitative predictors. For example, radiation flux correlated with surface temperature is commonly used in earlier research (Hossain and Takhar 1996; Santanello and Friedl 2003). Some research has attempted to use a regression model to explain the UHI effect by means of net radiation (Djen et al. 1994; Blankenstein and Kuttler 2004).

In this research, we derived a multi-variable regression from analyzing the traffic volume impact on the UHI effect, whereby the COVID-19 lockdown traffic control is included as the dummy variable. Defining the dummy variable allows us to capture the information of policy control in a categorization scheme and then to use the information in a standard regression estimation. When the COVID-19 lockdown variable is qualitative, we adopt a dummy variable that allows us to represent this policy information in a quantitative radiation-temperature model without imposing unrealistic measurement assumptions on the categorical variables. The logic of regression estimation remains the same: we are predicting conditional means on the dependent variable. We believe the COVID-19 lockdown, which limited the urban region's traffic volume, influenced the UHI effect in quantity and intensity—as vehicle exhaust is one of the most important sources of greenhouse gas that traps the emitted thermal radiation more effectively. In the regression model, the COVID-19 lockdown is utilized as a dummy variable under two conditions: (1) to set the dummy variable of the regression equation to the percentage of the traffic reduction during the period that the COVID-19 lockdown is imposed; or (2) to set the dummy variable to one or 100% for those time points without the COVID-19 lockdown. In that case, the dummy variable analysis reveals both whether the COVID-19 lockdown effects are statistically significant and what the quantitative effects of the traffic lockdown are on the UHI effect.

3.2 Statistical Regression Model with Radiation, LST (MODIS), and Traffic Variation

The intensity of solar radiation varies with the time and weather conditions and naturally influences the intensity and spatial extent of the UHI. In previous studies, the relationship of the LST with the solar radiation flux has been modeled to depict urban heat dynamics (Kato and Yamaguchi 2005). Some studies have also attempted to explain urban surface temperature variation by reference to solar radiation (Rizwan et al. 2008; Heat and Mitigation 2005) through a regression model. In this study, we use solar radiation to represent the natural effect of the sun on UHI dynamics.

Multivariate linear regression models were developed to analyze the variation of intensity of UHI in terms of mean temperature with solar radiation and traffic volume on the assumption that other factors that influence the heat environment are unchanged during our study period. According to the TIMS's traffic monitoring records for the six Bay Area counties, we define the UHI intensity using the mean LST over each single county, which was calculated and used as the UHI intensity in degrees Celsius. The mean value (intensity) for each county was then regressed with radiation including the COVID-19 lockdown dummy variable, which is expressed as:

$$T^{intensity} = A_0 + A_1 R^{solar} + A_2 D^{lockdown} + e_t \qquad (1)$$

where $T^{intensity}$ is the dependent variable of UHI intensity for a ring road zone. R^{solar} and $D^{lockdown}$ are as previously defined, while in this model variable $D^{lockdown}$ explains the COVID-19 lockdown effect on the UHI intensity. A_0, A_1, and A_2 are coefficients to be estimated. e_t is an error term.

3.3 Statistical Analysis Results

The statistical model aims to examine the influence of traffic volume on UHI intensity. We acquired the LST from MODIS for "lockdown" in 2020, as well as for "no lockdown" in 2019 as the control group; we constructed the model that investigates the cloud-free days. We built this model to test the influence of the traffic volume for six different Bay Area counties (see Figure 1), that is, San Francisco County, Santa Clara County, San Mateo County, Marin County, Contra Costa County, and Alameda County. The mean LST value of each county was calculated from the MODIS thermal remote sensing data over the 2020 COVID-19 lockdown, as well as the same period in 2019 as the control group. Each group's LST temperature is regressed with solar radiation and the percentage of the traffic volume monitoring records.

Table 5. Regression Results for Modeling of UHI Intensity in the Mornings

County	Regression model	R^2
San Francisco	$T^{mean} = 0.026 \times R_{Solar} - 0.26 \times D^{lockdown} + 12.71$	0.297
Santa Clara	$T^{mean} = 0.049 \times R_{Solar} + 0.41 \times D^{lockdown} - 0.05$	0.598
San Mateo	$T^{mean} = 0.033 \times R_{Solar} - 0.89 \times D^{lockdown} + 3.94$	0.431
Marin	$T^{mean} = 0.035 \times R_{Solar} - 0.15 \times D^{lockdown} + 4.07$	0.451
Contra Costa	$T^{mean} = 0.043 \times R_{Solar} - 4.78 \times D^{lockdown} + 6.00$	0.493
Alameda	$T^{mean} = 0.045 \times R_{Solar} - 1.53 \times D^{lockdown} + 3.87$	0.561

Table 6. Regression Results for Modeling of UHI Intensity in the Afternoons

County	Regression model	R^2
San Francisco	$T^{mean} = 0.023 \times R_{Solar} - 0.31 \times D^{lockdown} + 15.23$	0.269
Santa Clara	$T^{mean} = 0.051 \times R_{Solar} + 0.36 \times D^{lockdown} + 3.62$	0.533
San Mateo	$T^{mean} = 0.032 \times R_{Solar} - 0.34 \times D^{lockdown} + 9.77$	0.385
Marin	$T^{mean} = 0.039 \times R_{Solar} - 2.94 \times D^{lockdown} + 6.82$	0.415
Contra Costa	$T^{mean} = 0.049 \times R_{Solar} - 7.16 \times D^{lockdown} + 8.06$	0.565
Alameda	$T^{mean} = 0.045 \times R_{Solar} - 1.96\times D^{lockdown} + 7.83$	0.524

Tables 5 and 6 show the regression results for the morning and afternoon groups, respectively. Apparently, the multi-variable regression model fits a linear relationship between radiation, traffic variation, and UHI intensity. During the COVID-19 lockdown, the $D^{lockdown}$ displayed all negative effects for all counties except Santa Clara. For the morning group model, the $D^{lockdown}$ COVID-19 lockdown traffic reduction led to 0.263°C, 0.887°C, 0.146°C, 4.779°C, and 1.53°C reduction of the land surface temperature; meanwhile, for the afternoon group, the $D^{lockdown}$ COVID-19 lockdown traffic reduction led to a 0.308°C, 0.34°C, 2.941°C, 7.16°C, and 1.96°C reduction of the land surface temperature. The magnitude of the surface temperature reduction is consistent for the morning and afternoon groups.

Three counties on the west side of the Bay Area (San Francisco, San Mateo, and Marin) show a smaller temperature reduction, less than 1°C in terms of the LST temperature reduction. On the other hand, two counties on the east side of the Bay Area (Contra Costa and Alameda) show a larger temperature reduction, 4.78°C and 7.16°C for Contra Costa and 1.53°C and 1.96°C for Alameda, respectively. This might be due to the different microclimates on each side of the Bay (Ekstrom and Moser 2014). The East Bay usually gets colder and wetter weather than the peninsula, due to various levels of the influence of the ocean (Keeley 2005).

An outlier is Santa Clara County in the South Bay, which results in a positive impact on the deduction of traffic. That is, the traffic reduction during the lockdown actually caused a land surface temperature increase compared to the control group without the lockdown. This trend is also consistently presented in both morning and afternoon groups. The reason for this phenomenon needs to be further investigated in future research. Besides the location of Santa Clara in the south Bay Area, another factor that should be considered is that Santa Clara is the most populous county in the San Francisco Bay Area and in Northern California as a whole. The lockdown policy implementation might also cause other anthropogenic heat generation from people staying home.

4. Discussion and Conclusions

In this study, we derived a multi-variable regression model based on the UHI intensity from remote sensing LST and solar radiation data during 2019 and 2020 with the COVID-19 lockdown. The lockdown was included as a dummy variable in the statistical model to quantitatively evaluate traffic reduction on the UHI intensity. During the COVID-19 lockdown, the traffic volume was regulated and reduced by 30–50% according to the UC Berkeley TIMS traffic dataset. Statistical models have been constructed using a dummy variable to indicate the COVID-19 lockdown. The results of the analysis suggest that a decrease in urban traffic volume can significantly reduce the intensity of the UHI. When the COVID-19 lockdown cut traffic volume, UHI intensity was reduced by an average of 1.52°C and 2.54°C for the morning and afternoon, respectively. This UHI reduction brought about by the COVID-19 lockdown was more effective in the East Bay Area than in the West Peninsula. The South Bay showed a contrary pattern for the LST reduction. This study is the first attempt to quantify the impact of traffic on the UHI, providing an important milestone for quantifying the contribution of traffic volume as a significant anthropogenic factor to the UHI and, hence, climate change.

A comparison was also made between the morning and the afternoon groups. Overall, the results show that the afternoon group has a greater decreased temperature and a larger extent than the morning group. Moreover, the morning group has a higher average r^2 value than the afternoon group. For the UHI intensity model, the morning group has a lower average r^2 value than the afternoon group. For the extent-based model, traffic impacts on UHI afternoon have a smaller r^2 value than the morning model. To explain this, the time of the morning group (10:30 AM) is close to the morning rush hour, while the time of the afternoon group (1:30 PM) is removed from rush hour. Therefore, the morning group could be influenced more by the traffic factor because the larger traffic volume on the road could cause a more significant expansion of the UHI extent. On the other hand, the intensity-based model could be more influenced by solar radiation since we measure the mean temperature for each zone. The solar radiation absorbed by the urban surface around 1:30 PM is remarkably stronger than around 10:30 AM. The reduced traffic volume's effects on the UHI could be diminished by the much stronger radiation absorbed by the Earth.

Other factors have also been taken into consideration, such as wind speed and water bodies. Including the COVID-19 lockdown as the dummy variable provides the estimation of UHI intensity changes caused by traffic. It has been demonstrated that the greenhouse gas emitted by vehicle exhaust is one of the most important factors that causes climate change, but it is still unclear how vehicles contribute to urban climate change (Ren et al. 2015; Amato et al. 2014; Czarnecka and Nidzgorska-Lencewicz 2014). This research only discussed climate change in the context of vehicular traffic flow. Detailed factors such as vehicle exhaust, gas emissions such as carbon-based molecules or water vapor (another potent greenhouse gas), particulates, engine heat, or emissivity change by the vehicle metal body are not explored in this study. The radiation data used in this study is total solar radiation from the meteorology station. For future research, we will try to access the net radiation to further improve the energy budget model.

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